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# Modeling the luminous intensity of Beijing, China using DMSP-OLS night-time lights series data for estimating population density

Pavan Kumar[a,*], Haroon Sajjad[a], P.K. Joshi[b], Christopher D. Elvidge[c], Sufia Rehman[a], B.S. Chaudhary[d], Bismay Ranjan Tripathy[e], Jyoti Singh[f], Gajendra Pipal[g]

[a] Faculty of Natural Science, Department of Geography, Jamia Millia Islamia, New Delhi, India
[b] School of Environmental Science, Jawaharlal Nehru University, New Delhi, India
[c] Applied Earth Sciences, National Oceanic and Atmospheric Administration, Stanford University, Boulder, CO 80305, USA
[d] Department of Geophysics, Kurukshetra University, Kurukshetra, Haryana, India
[e] National Centre for Earth Science Studies Earth System Science Organization, Thiruvananthapuram, Kerala, India
[f] Forest and Ecology Group, National Remote Sensing Centre, Balanagar, Hyderabad, India
[g] Punjab Remote Sensing Centre, Ludhiana, Punjab, India

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ABSTRACT

Various scientific researches were conducted to monitor human activities and natural phenomena with the availability of various night time satellite data such as Defense Meteorological Satellite Program (DMPS). Population growth especially in a faster growing economy like China is an important indicator for assessing socio-economic development, urban planning and environmental management. Thus, spatial distribution of population is instrumental in assessing growth and developmental activities in Beijing city of China. The satellite observation data derived from Defense Meteorological Satellite Program (DMSP) was utilized to estimate population density through the measurement of light flux with radiometric recording. The data was calibrated using $C_0$, $C_1$, $C_2$ parameters before processing. Population density of Beijing city was estimated using light volume of this calibrated data. Regression analysis between urban population and light volume revealed high correlation ($r^2 = 0.89$). Thus, population density can effectively be estimated using light intensity. The model used for estimating urban population density can effectively be utilized for other major cities of the world.

## 1. Introduction

Population growth has been used by many scholars as a significant parameter forassessing socio-economic development, urban planning, environmental management and sustainable development and management of resources (Zhuo et al., 2009; Zeng et al., 2011; Ma et al., 2012, 2015; Yu et al., 2014; Gao et al., 2015). Urban population in China has increased from 17.9% in 1978 to 57.35% in 2016 (United Nations, 2015). An increase in its population is projected to be 60% by 2020 (National Bureau of Statistics of the People's Republic of China, 2017). This tremendous increase in urban population has increased the demand for energy consumption, (Tripathy et al., 2018; Zhang, 2015; He et al., 2012; Dobson et al., 2000), land transformation (Li et al., 2016; Wang et al., 2017), shortage of food supply (Obienusi et al., 2014, Hutchinson and Hutchinson, 1969), emissions from household garbage (Atasoylu et al., 2007) anddomestic water use (Yigzaw and Hossain, 2016). The exponential increase in population has put stress on food safety (János, 2014), ecological environment (Elvidge et al., 1997a,b; Miao et al., 2016) and sustainable development (János, 2014). Thus, scientific assessment of human population distribution in case of developing nation is immensely important (Pan et al., 2016). Urbanization is increasingly gaining interest among policy makers and researchers alike. Urban areas are being included among other indicators for assessing economic development, sources of environmental and climate change pressure and crime hotspots (Pandey et al., 2013; Raupach et al., 2010).

Light at night is like a Miniature Sun that makes everyone and everything appears to be at its best and at the same time enhances workplaces as well as surroundings. Scientists have worked foryears to betray the new prospect of looking at our planet at night (Lu et al., 2008; Jing et al., 2015). A number of satellites across globe are available to observe the earth during day at the cost of light delivered by the

* Corresponding author.
*E-mail addresses:* pawan2607@gmx.com (P. Kumar), haroon.geog@gmail.com (H. Sajjad), pkjoshi27@hotmail.com (P.K. Joshi), chris.elvidge@noaa.gov (C.D. Elvidge), srfpinky@gmail.com (S. Rehman), bschaudhary@kuk.ac.in (B.S. Chaudhary), bismaytripathy@outlook.com (B.R. Tripathy), jyoti.singh8808@gmail.com (J. Singh), Gajendra.pippal50@gmail.com (G. Pipal).

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sun. Operational Linescan System (OLS) images help in providing night time visualization of the earth surface. United States Air Force Defence Meteorological Satellite Program Operation Line scan System (DMSP-OLS) night-time light images have largely been utilized to monitor urbanization dynamics since two decades (Elvidge et al., 1997a,b, 2007a,b; Lo, 2001; Liu et al., 2012, Witmer and O'Loughlin, 2011). The global composite cloud free images obtained through National Oceanic and Atmospheric Administration (NOAA) enableto have a synoptic view of sparkling light being emitted from the area inhabited by humans. The advent of such satellite has made it possiblescientists to observe the planet Earth even at night and made us to be staunch supporter of "Nothing tells us more about the spread of humans across the Earth than city lights" (Elvidge, 1999). For the lastfour decades, the satellites in the U.S. Defence Meteorological Satellite Program (DMSP) have been making observations with the low light sensors. Assessment of clouds, storms and smoke plumes at each and every hour of a day has been driving force for the introduction of low light earth observations. Night light data is user friendly for studying the various aspects of population for identifying urban and modelling different socio-economic parameters (Kumar et al., 2017; Tripathi et al., 2017; Doll and Muller, 1999; Levin and Duke, 2012; Christopher et al., 2006; Sutton, 1997). Population is unevenly distributed over the earth's surface mainly due to varied climatic and topographical conditions. Elvidge (2009) in late 1960s suggested that settlement size can be helpful in assessing human population in any defined region (Sutton et al., 2009; Elvidge et al., 2009; Jenerette et al., 2007).

Settlement modelling as circular areas can be beneficial in evaluating population by establishing empirical relationship. The night light imageryhas become an important source forestimating the population of an area and is largely used for studying socio-economic properties, population distribution and density. (Sutton et al., 1997; Ghosh et al., 2009; Elvidge et al., 1997a,b; Zhang and Hao, 2007; Small et al., 2005; Milesi et al., 2003; Bennett and Smith, 2017). The night time data has overcome the problem of using high spatial resolution data for identifying human settlement and has made possible to retrieve information during nighttime which definitely reflects more human activities (Sullivan, 1989; Doll et al., 2000, Ebener et al., 2000). Hence night-time satellite data can help in detecting the population of an area.

Supremely the population censuses are held regularly in five or ten year'sintervalsin a country. An acquaintance of the size and dissemination of human population is important for empathetic and retorting to many social, political, economic and environmental problems (Li et al., 2013a,b). Remote sensing and GIS have been used since many years to assess population for different areas or regions. Interpolation method and geo-statistical modelling have largely been used for assessing population (Hu, 2016; Xu et al., 2014; Ma et al., 2014). Night time light satellite data can detect presence of human on the earth. The data is used after the calibration of satellite data for each year. This paper makes an attempt to estimate urban population using night time light data in Beijing, China.

The aim of the paper is to quantify the pixel level spatio-temporal pattern and trend of urbanization in Beijing by analysing the night-time light data during 1992–2013 derived from DMSP-OLS. Urbanization was viewed as comprised of urban land cover including the urban population activities as represented by elevated night-time light brightness.

## 2. Material and methodology

### 2.1. Study area

Beijing, the capital of the People's Republic of China having an area about 16,400 $km^2$ is situated in north China plain between 39°28′N to 41°05′N latitudes and from 115°25′E to 117°30′E longitudes (Fig. 1). Most of the area of the city (62%) is under mountain and nearly 32% area is under plain topography. Beijing has experienced an increase of about 44% in population during the last decade (Sumita, 2011). The total population of Beijing is 2.1 million with a population density of 1525 population/$km^2$.

Beijing enjoys a continental monsoon climate having four distinct seasons. Winter and summers are of longer duration while spring and autumn is of short duration. The city receives an average annual rainfallof 572 mm and records an annual temperature of 12.3 °C. Beijing is one of the tenth major metropolitan cities enjoying 1378 billion gross domestic products (Beijing Statistical Year book, 2017). Beijing city has complex and diversified landscape. Construction land, cultivated land and forest are the major land uses of the city (Huilei et al., 2017). The city has multi-functions and it is a centre for political activities, education and culture. The city witnessed large scale urbanization during 2000–2010. One of the conspicuous changes in the city was increased in the construction of urban and rural land. Thus, rapid urbanization urged to estimate urban population in the city using night time light data.

### 2.2. Data used

Operational Linescan System (OLS) and photo multiplier tube (PMT) datahaving 3000 km swath width was used in the study. The spatial resolution of captured images is 2.7 km and 6-bit radiometric resolution. Numbers of observations were influenced by thefactors like clouds and moonlightand the composites with a timeframe of a year failed to provide observations apart from a particular year. Nearly twenty to hundred cloud free observationswere found in composite images. National Centres for Environmental Information (NCEI) of the National Oceanic and Atmospheric Administration (NOAA) data provided better quality products.

### 2.3. Inter calibration of DMSP data

The emitted or reflected electromagnetic energy is greatly influenced by theSun's azimuth angle, elevation and atmospheric conditions like fog, dust particles, or aerosols, etc. Hence, the observed energy that is recorded from a short distance for a particular object does not coincide with the same observed object recorded by the onboard sensor on an aircraft. Care must be taken when the comparison between images of different years is carried out. Captured images obtained from the same satelliteare largely susceptible to natural deterioration of the sensor over time resulting inundocumented gain adjustments. These kinds of errors were corrected following the methods used by Li et al. (2013a) and Wu et al. (2013). Hence, three calibrating parameters ($C_0$, $C_1$, $C_2$) were calculated for each satellite. Thus, the old DN ($DN_{old}$) values were computed to new inter calibrateddigital numbers ($DN_{new}$) for each image using the following equation:

$$DN_{new} = C_0 + C_1 * DN_{old} + C_2 * (DN_{old})^2 \quad (1)$$

Calculated inter-calibration model coefficients of each phase of the images are shown in Table 1. All the analysis was undertaken using the raster package within the R computing environment (Hijmans and Etten, 2011). The steps used for obtaining luminous intensity of Beijing city for estimating population density has been presented in Fig. 2.

### 2.4. Luminous intensity and emission

Wave length in the visible spectrum was considered for measuring visible light. Wavelength is inversely proportional to energy. Shorter the wave length higher is the energyand vice-versa. Visible light was measured using photometry. Histogram was used to show the peaks in distribution which helped in estimating classes and their ranges respectively. The imagewasthen classified using ISODATA algorithm in ENVI 5.0 (Environment for Visualizing Images). Light intensity helped in visualizing the spatial distribution of population over the space and modelling the population. Assessing indoor scenes through light

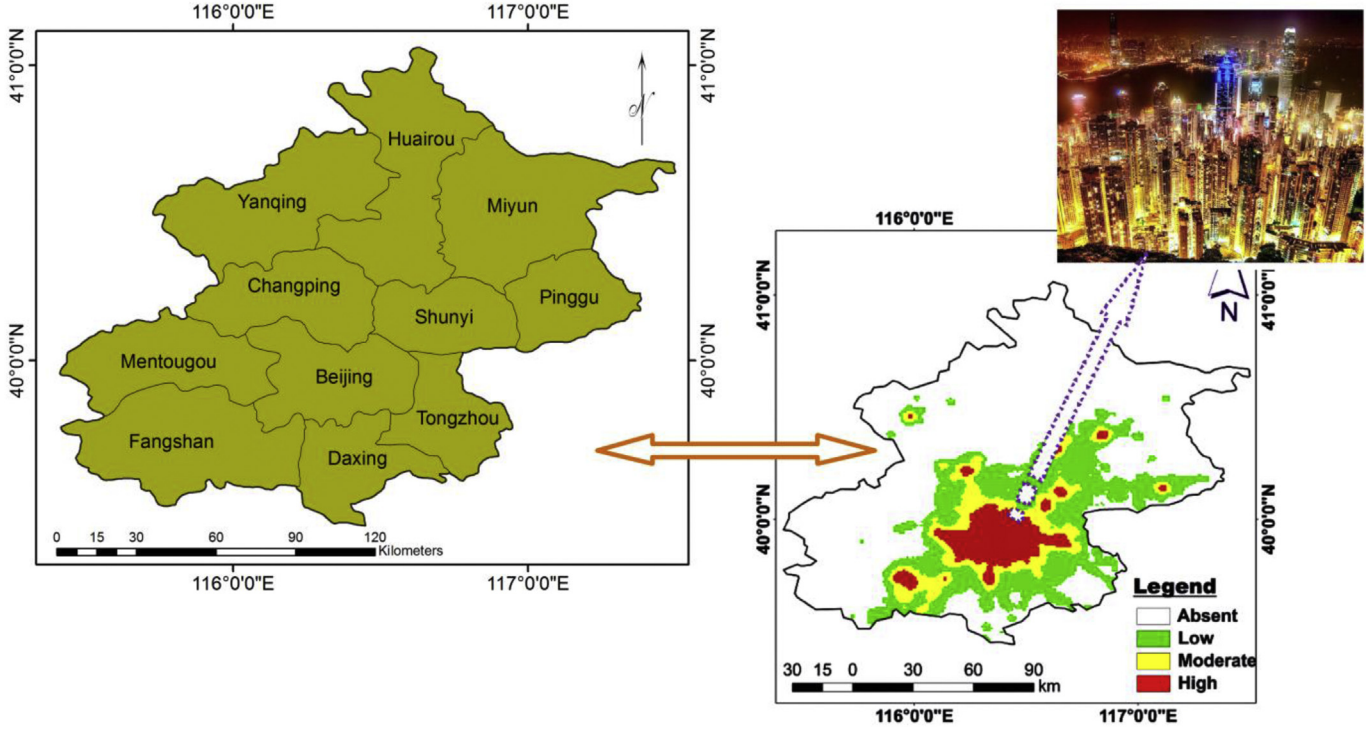


**Fig. 1.** Location map of study area.

**Table 1**
Constant and coefficient data for calibration.

| Satellite | Year | $C_0$ | $C_1$ | $C_2$ | $R^2$ |
|---|---|---|---|---|---|
| F10 | 1992 | −2.05696 | 1.59028 | −0.00896 | 0.9821 |
| | 1993 | −1.05821 | 1.59826 | −0.00929 | 0.9976 |
| | 1994 | −0.34581 | 1.48639 | −0.00791 | 0.9998 |
| F12 | 1994 | −0.68901 | 1.17701 | −0.00251 | 0.9934 |
| | 1995 | −0.05154 | 1.22932 | −0.00377 | 0.9965 |
| | 1996 | −0.09593 | 1.2727 | −0.00403 | 0.9812 |
| | 1997 | −0.33206 | 1.1782 | −0.00262 | 0.9954 |
| | 1998 | −0.06078 | 1.06477 | −0.00128 | 0.9937 |
| | 1999 | −2.85E-14 | 1 | −1.31E-16 | 0.9983 |
| F14 | 1997 | −1.13232 | 1.76963 | −0.0122 | 0.9828 |
| | 1998 | −0.19165 | 1.63206 | −0.01007 | 0.9994 |
| | 1999 | −0.15575 | 1.50548 | −0.00779 | 0.9862 |
| | 2000 | 1.09879 | 1.31553 | −0.00527 | 0.9890 |
| | 2001 | 0.19426 | 1.32185 | −0.00512 | 0.9923 |
| | 2002 | 1.05166 | 1.19048 | −0.0036 | 0.9841 |
| | 2003 | 0.739017 | 1.24156 | −0.00396 | 0.9927 |
| F15 | 2000 | 0.125402 | 1.04518 | −0.00102 | 0.9865 |
| | 2001 | −0.70239 | 1.10808 | −0.00124 | 0.9984 |
| | 2002 | 0.049067 | 0.95678 | 0.001003 | 0.9951 |
| | 2003 | 0.221673 | 1.51216 | −0.00795 | 0.9878 |
| | 2004 | 0.575092 | 1.33346 | −0.00511 | 0.9794 |
| | 2005 | 0.636684 | 1.28376 | −0.00413 | 0.9909 |
| | 2006 | 0.826146 | 1.27898 | −0.00406 | 0.9945 |
| | 2007 | 1.36055 | 1.29738 | −0.00452 | 0.9768 |
| F16 | 2004 | 0.285342 | 1.19548 | −0.00344 | 0.9751 |
| | 2005 | −9.25E-05 | 1.41585 | −0.00627 | 0.9948 |
| | 2006 | 0.106462 | 1.13706 | −0.00161 | 0.9995 |
| | 2007 | 0.639386 | 0.91143 | 0.001379 | 0.9901 |
| | 2008 | 0.556371 | 0.993082 | 5.46E-06 | 0.9948 |
| | 2009 | 0.949171 | 1.06833 | −0.00156 | 0.9721 |
| F18 | 2010 | 2.34298 | 0.510197 | 0.006467 | 0.9802 |
| | 2010 | 2.34581 | 0.509999 | 0.00647 | 0.9739 |
| | 2011 | 1.89559 | 0.734502 | 0.003021 | 0.9861 |
| | 2012 | 1.87503 | 0.620317 | 0.005186 | 0.9903 |
| | 2013 | 1.84108 | 0.70493 | 0.003314 | 0.9948 |

estimation is challenging in computer visualization. However, multiple light sources of different intensities, spectral characteristics, shape and size are considered essential in analysing spatial distribution of population.

Alternative algorithms are sometimes failed to assess the low-quality images. Decomposing an original image into secular shading, diffuse shading and albedo are helped in assessing these images. Changing light configuration of two shading images was utilized to render different version of original image. Light condition helped in reducing the variation between original and render images. Yearly population and DMSP data for Beijing is presented in Table 2. Arc GIS software was used to classify the raw image into several classes. Highest DN value of particular class has been multiplied by the area to find out volume (Eqs. (2)–(5)).

### 2.5. Light volume

Evaluation of light volume of night time data requires the multiplier (m) of each class including highest occurring DN value of any class. Light volume was obtained byutilizing the class area and multiplier (m). LV refers to the light volume of a night time image:

$$V_1 = m_1 \times cl_1 \quad (2)$$

$$V_2 = m_2 \times cl_2 \quad (3)$$

$$V_3 = m_3 \times cl_3 \quad (4)$$

$$LV = V_1 + V_2 + V_3.....V_n \quad (5)$$

### 2.6. Modeling of population estimation

Strong correlation between population and light intensity suggest that population increase is associated with increasing urban expansion and built-up area. We can derive the degree of relationships among DMSP night light volume with a non-agricultural population of a province. Regression analysis was used for assessing built-up expansion of images:

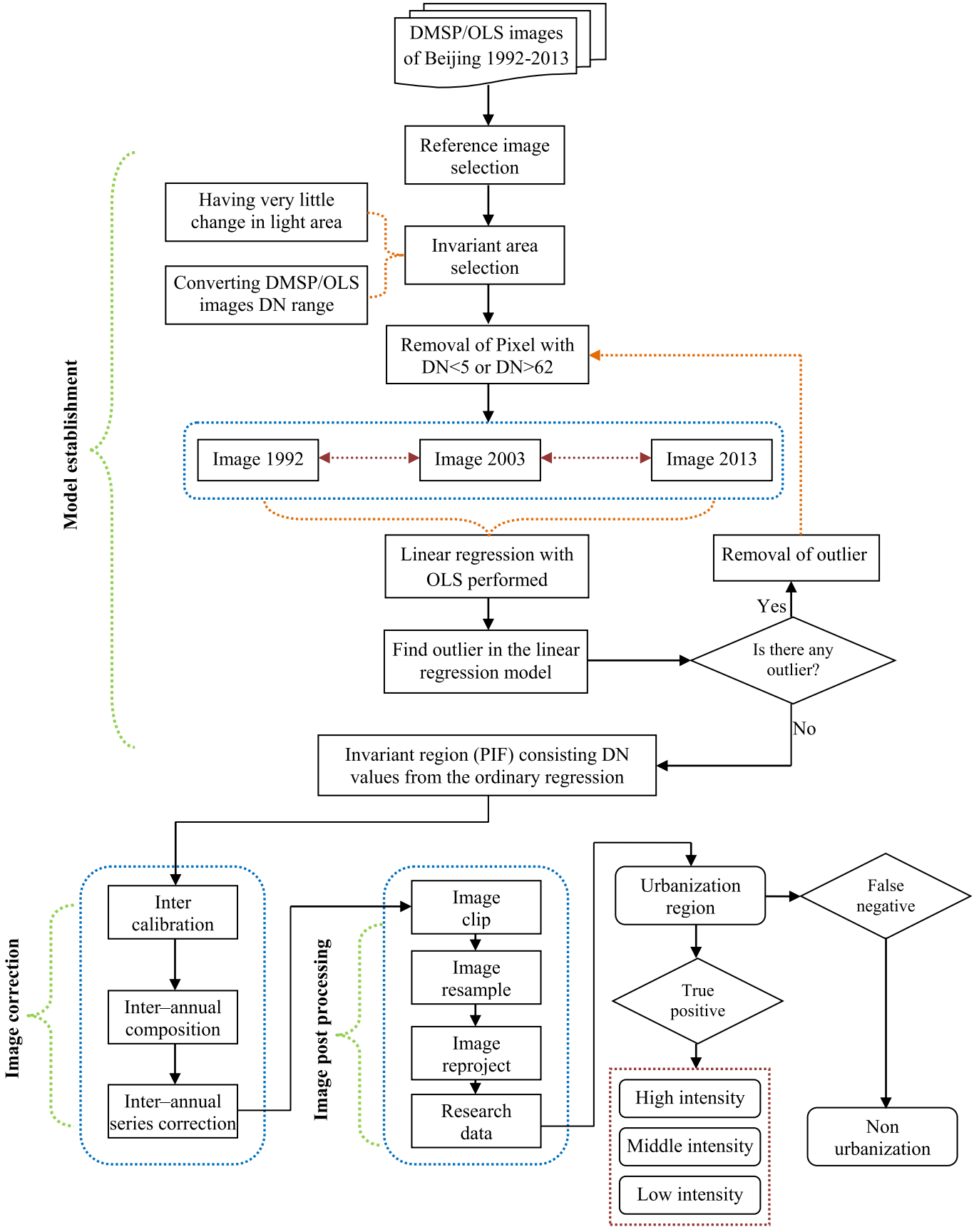


**Fig. 2.** Analytical approach to obtain luminous intensity of Beijing.

**Table 2**
Defence Meteorological Satellite Program (DMSP) data characteristics and yearly urban population density.

| Year | Light Area | Light Volume | Urban Population (million) | Urban Population Density (population/km$^2$) |
|---|---|---|---|---|
| 1993 | 12154 | 198598 | 8.31 | 506.38 |
| 1994 | 12108 | 203714 | 8.46 | 515.52 |
| 1995 | 12325 | 209825 | 8.86 | 563.24 |
| 1996 | 10114 | 210124 | 9.579 | 583.71 |
| 1997 | 10214 | 219824 | 9.643 | 587.25 |
| 1998 | 10952 | 209985 | 9.701 | 591.96 |
| 1999 | 11530 | 209610 | 9.717 | 592.12 |
| 2000 | 11758 | 236524 | 10.19 | 632.45 |
| 2001 | 11952 | 262145 | 10.92 | 667.21 |
| 2002 | 12140 | 282132 | 11.18 | 681.27 |
| 2003 | 12265 | 302154 | 11.57 | 704.69 |
| 2004 | 12278 | 319891 | 11.872 | 723.44 |
| 2005 | 12376 | 332879 | 12.861 | 783.70 |
| 2006 | 12465 | 345124 | 12.893 | 785.34 |
| 2007 | 13201 | 351442 | 12.915 | 786.99 |
| 2008 | 11159 | 354658 | 13.34575 | 813.24 |
| 2009 | 12126 | 360916 | 14.76788 | 899.90 |
| 2010 | 14256 | 382154 | 15.658 | 954.25 |
| 2011 | 15113 | 406645 | 16.987 | 1035.13 |
| 2012 | 16542 | 462548 | 17.658 | 1065.21 |
| 2013 | 18164 | 469841 | 18.0355 | 1099.02 |

$$Population = Constant + Coefficent \times (LV) \tag{6}$$

### 2.7. T-testand null hypothesis ($H_0$)

T-test was applied for determining the two sets of data that are significantly different from each other. It is a statistical hypothesis test, in which the Student's t-distribution under the null hypothesis is followed. On the basis of distribution, the variance may or may not have a statistically significant difference. Hence, we require a parameter for the testing, which is the ratio of signals to noise, i.e. t-value. A t-statistics with n degree of freedom is, by definition, a variable of the form:

$$t = \frac{x}{\sqrt{\frac{y^2}{n}}} \tag{7}$$

Where $x$ is a normal variable with zero mean and unit variance, while $y^2$ is a$x^2$ with n degrees of freedom and is independent of $x$. the joint distribution of x and $y = +\sqrt{y^2}$ has the p. d.f.

$$\frac{1}{\sqrt{2\pi 2^{\frac{n-2}{2}}\tau\left(\frac{n}{2}\right)}} \exp\left[-\frac{1}{2}(x^2+y^2)\right] y^{n-1}, \quad for$$
$$-\infty < x < \infty, \quad 0 < y < \infty \tag{8}$$

The polar transformation (x,y)→(u, $\theta$) such that the t-statistics are used for

$$x = u\cos\theta, \quad (0 < u < \infty)$$
$$y = u\sin\theta, \quad (0 < \theta < \pi)$$

Also, the statistics say, $x^2 + y^2 = u^2$ and $J\left(\frac{x,y}{u,\theta}\right) = u$.

Hence, the joint p. d.f. of $u$ and $\theta$ is

$$\frac{1}{2^{\frac{(n-1)}{2}}\sqrt{n\tau\left(\frac{n}{2}\right)}} \exp\left[-\frac{1}{2}u^2\right] u^2 sin^{n-1}\theta, \quad for \quad 0 < u < \infty, 0 < \theta < \pi \tag{9}$$

The (marginal) p.d.f. of $\theta$ is, then,

$$CSin^{(n-1)}\theta, \quad for \ 0 < \theta < \pi$$

Where the constant C may be determined from the condition

$$C\int_0^{\pi} Sin^{n-1}dx = 2C\int_0^{\frac{\pi}{2}} Sin^{n-1}\theta d\theta, \text{ which is equal to C X B}\left(\frac{n}{2}, \frac{1}{2}\right) = 1$$

This gives

$$C = \frac{\tau\left(\frac{n+1}{2}\right)}{\sqrt{nT\left(\frac{n}{2}\right)}} \tag{10}$$

We are interested in the distribution of t-statistics, where $t = \sqrt{n}\cot\theta$.

Since, $\theta = \cot^{-1}\frac{1}{\sqrt{n}}$

$$\frac{d\theta}{dt} = \frac{1}{\sqrt{n}\left(1+\frac{t^2}{n}\right)}$$

When sampling from the same population is approximately 0.006 then the probability of obtaining a t-value would be 2.8 or higher

$$t - \text{value} = \frac{signal}{noise} = \frac{|\overline{X_1} - \overline{X_2}|}{\sqrt{\frac{S_1^2}{n} - \frac{S_2^2}{n}}} \tag{11}$$

For testing, we start with the null hypothesis that there is no statistical significance between the samples. Null hypothesis in inferential statistics indicates that there is no relationship between any two measured phenomena or group. By rejecting the $H_0$, we can conclude that, there must be a relation between two phenomena, whichis light volume and the population.

## 3. Results and discussion

### 3.1. Determination of inter calibration

The data during 1992–2013 were calibrated using linear regression with the help of parameters provided by National Centres for Environmental Information (NCEI). The coefficient of determination and roo tmean square error (RMSE) were considered to reduce the effect of the outlier most effectively. Fig. 3 shows the DN numbers before and after the calibration process. RMSE were observed to be very negligible suggesting the linear regression models much accurate (see Fig. 4).

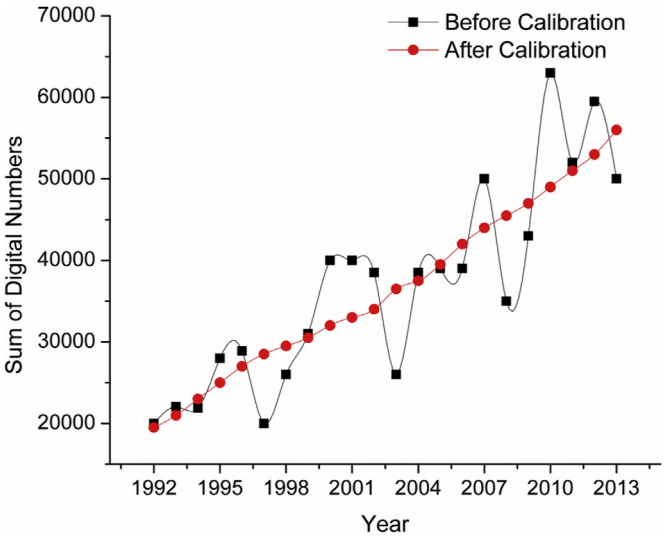


**Fig. 3.** Sum of digital numbers (DNs) from 1992 to 2013 before and after calibration.

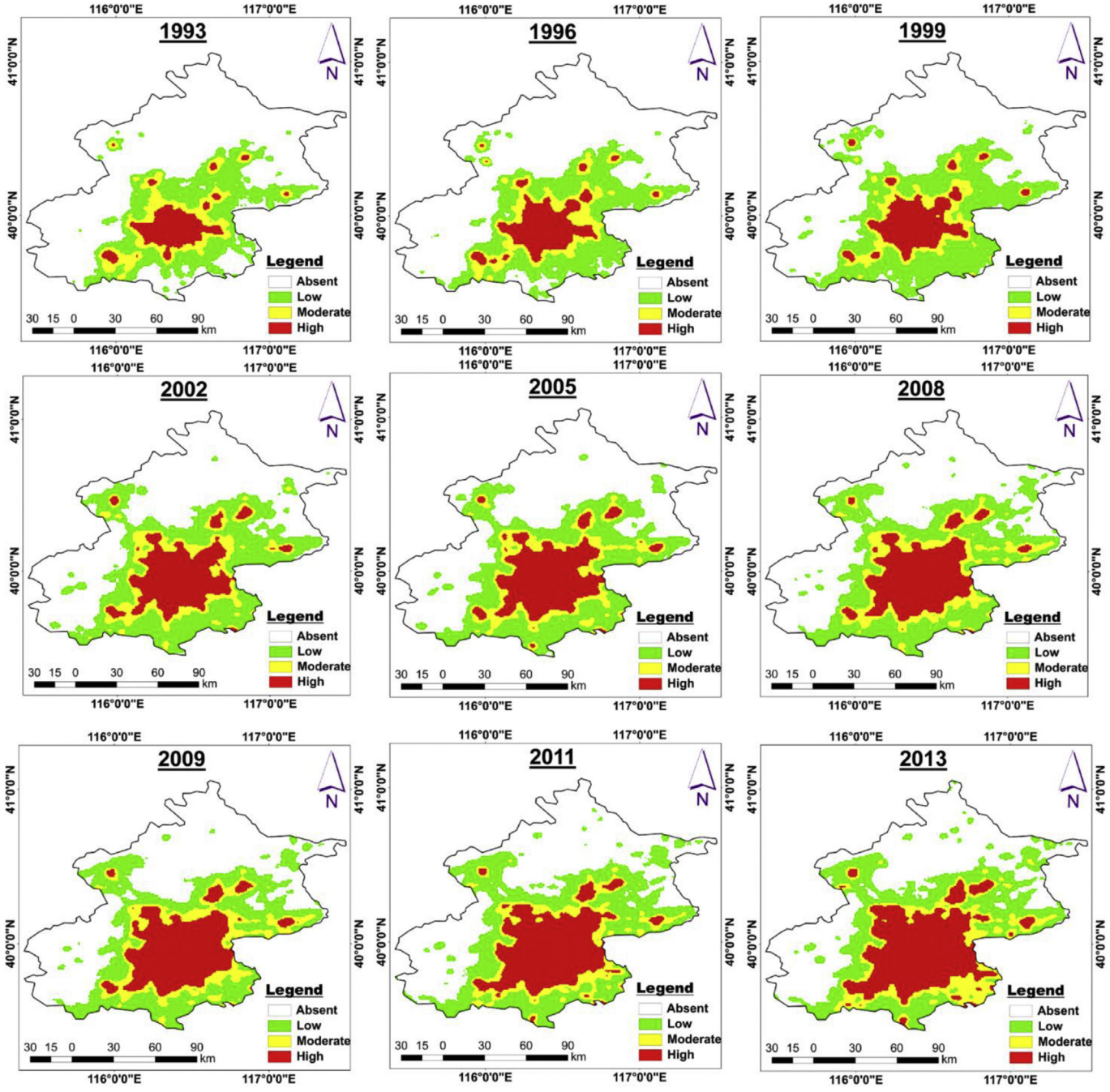


**Fig. 4.** Luminous intensity map of Beijing.

### 3.2. Luminous intensity

Luminous intensity maps during 1992–2013 revealed that Beijing has been experiencing rapid urban expansion since early 1990s. The map was classified into four classes based on the light intensity. High light intensity in inner city of Beijing in all the maps during 1992–2013 indicated high population.

### 3.3. Urban population density per light area and volume

Light volume, light area and urban population density as three-dimensional parameters were plotted X, Y and Z axes. The value of light density exceeded the parameter of the light area and was directly proportional to the light volume. The highest magnitude of all these three parameters obtained from dynamic regression was placed on highest coordinate and elevated area (Red spline-sheet). The relatively lower magnitude value of this density study is plotted with lower elevated value (Green spline-sheet). The urban population density magnitude is the integral value as the solid angle was maximum than the other two axesvalues. Z-axis which is representing the urban population density is the magnitude value of the coordinate of other two values. The data of colour shades on the plot represents the density of stacking whiles the other two parameters denoting the binning of the resultant value on the graph. This interprets that the tiding of light volume over the light area is the resultant of third vector urban population density (see Fig. 5).

### 3.4. Analysis of variance (ANOVA)

ANOVA was utilized to find out the relationship between the means.

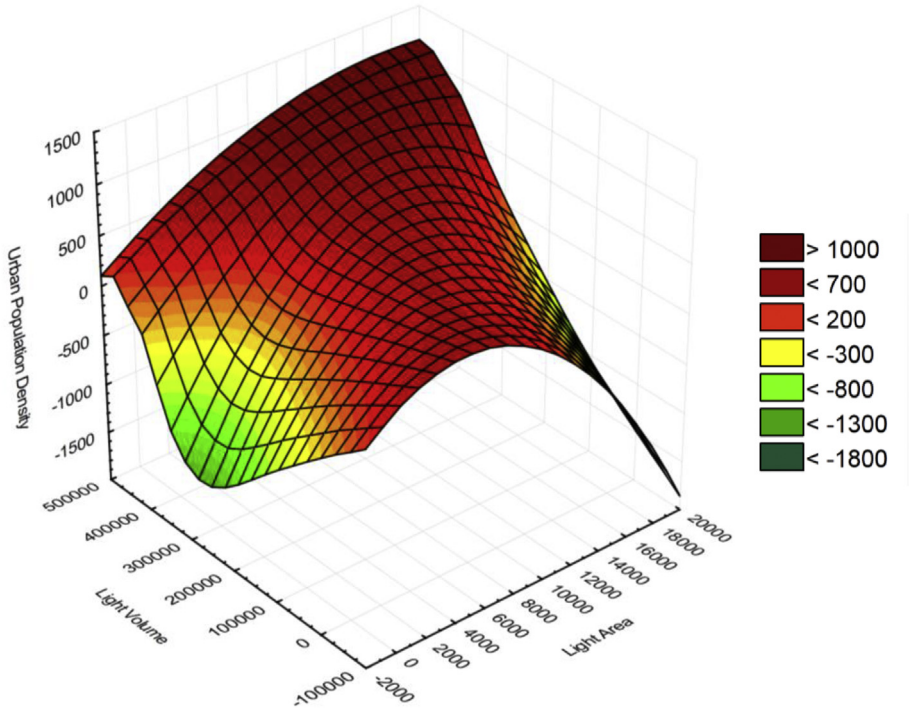


**Fig. 5.** Urban population density per light area and volume.

Thus, it helped to find out whether the means of several groups were equal or not. T-test was performed to achieve the statistical significance in more than two groups. Regression analysis between light volume and urban population revealed significant and strong relationship ($r^2$ = 0.89) with significance level (α) 0.05 (Fig. 6).

We analysed from the Fig. 6 and with the help of t-table that:

t-value = 6.1251,β value (*t*-test) = 1.812 with df = 10 (df: 12–2 = 10).

As t-value > β value evinces a statistical significance among the variables. The equation for population modelling is;

$$Pop = 38.23 * (LV) + 8018.4 \quad (12)$$

The data provided an opportunity to measure and map the population distribution where as raw format data was difficult to interpret. However, inter calibration method wasfound to be more significant than any radiometric normalization technique to create time series harmonious dataset for developing various human indexes.

## 4. Conclusion

This study used DMSP-OLS night time satellite data during 1992–2013 to characterize urbanization dynamics for Beijing, China. The human activities observed during night helped in assessing

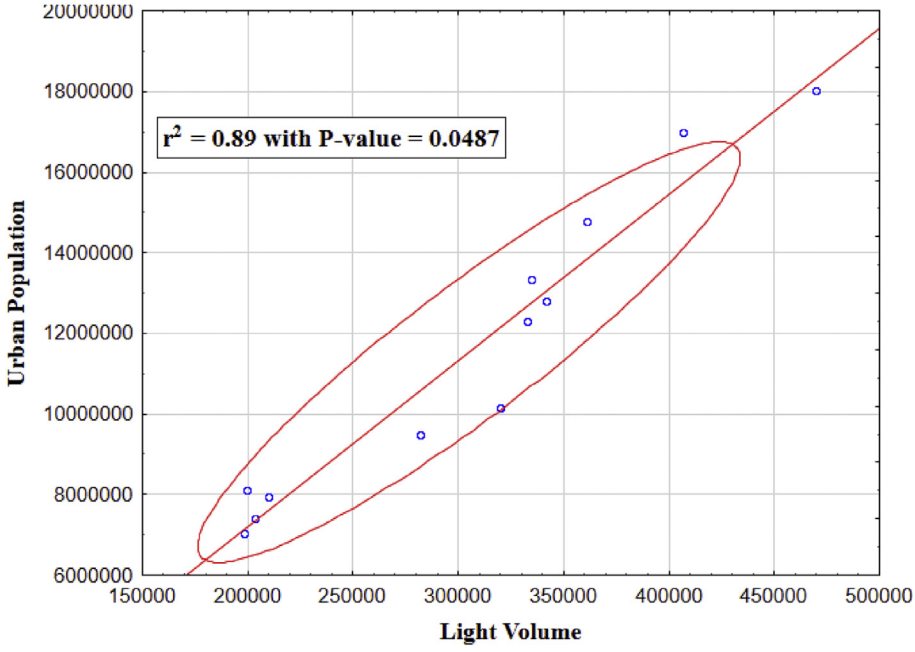


**Fig. 6.** Regression analysis between urban population and light volume with α = 0.05.

concentration of human population in the city. Luminous intesity maps revealed continuous increase in urban population. The estimation of urban population was verified by analyzing the relationship among urban population, light area and light volume. The analysis revealed that high urban population density was found in those areas where light volume and area was high. Such relationships are proved to be advantegeous and powerful tool in evaluating, modelling and monitoring the human population on a universal scale. DMPS-OLSdatabase can effectively be utilized for timely measurement of spatial expansion of urban areas and associated activities at various scales. Scope exists for enhancement and wider application such as extending the research to investigation between DMSP night time data to other human activities like energy consumption, city growth and GDP, etc. Thus, the research work carried out using the night time satellite data can prove to be a good source of information for further studies.

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## Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.pce.2018.06.002.

## References

Atasoylu, G., Evci, E.D., Kaya, E., Ergin, F., Tikir, D., Beser, E., 2007. The household garbage in the western coast region of Turkey and its relationship with the socio-economic characteristics. J. Environ. Biol. 28, 225–229.

Beijing Statistical Yearbook. Available online: http://www.bjstats.gov.cn/nj/main/2016-tjnj/zk/indexch.htm (Accessed on 1 November 2017).

Bennett, M.M., Smith, L.C., 2017. Advances in using multitemporal night-time lights satellite imagery to detect, estimate, and monitor socioeconomic dynamics. Remote Sens. Environ. 192, 176–197.

Christopher, N.H. Doll, Jan-Peter, Muller, Jeremy, MorleyG., 2006. Mapping regional economic activity from night-time light satellite imagery. Ecol. Econ. 57, 75–92.

Dobson, J.E., Brlght, E.A., Coleman, P.R., Durfee, R.C., Worley, B.A., 2000. Landscan: a global population database for estimating populations at risk. Photogramm. Eng. Rem. Sens. 66, 849–857.

Doll, C.N.H., Muller, J.P., 1999. The use of radiance calibrated night-time imagery to improve remotely sensed population estimation. In: Proceedings of the 25th Annual Conference of the Remote Sensing Society. University of Wales, Cardiff, UK 9–11 September. Remote Sensing Society, Nottingham, UK, pp. 127–133.

Doll, C.N.H., Muller, J.P., Elvidge, C.D., 2000. Night-time imagery as a tool for global mapping of socio-economic parameters and green house gas emission. Ambio 29, 157–162.

Ebener, S., Murray, C., Tandon, A., Elvidge, C., 2000. From welth to helth: modelling the distribution of income per capita at the sub-national level using night time lights imagery. 4, 5–11.

Elvidge, C.D., 1999. Radiance calibration of dmsp-ols low-light imaging data of human settlements. Rem. Sens. Environ. 68 (1), 77–88.

Elvidge, C.D., 2009. A global poverty map derived from satellite data. Comput. Geosci. 35, 1652–1660.

Elvidge, C.D., Baugh, K.E., Kihn, E.A., Kroehl, H.W., Davis, E.R., 1997a. Mapping city lights with nighttime data from the DMSP operational linescan system. Photogramm. Eng. Rem. Sens. 63, 727–734.

Elvidge, C., Baugh, K., Hobson, V., Kihn, E., Kroehl, H., Davis, E., Cocero, D., 1997b. Satellite inventory of human settlements using nocturnal radiation emissions: a contribution for the global toolchest. Global Change Biol. 3, 387–395.

Elvidge, C.D., Cinzano, P., Pettit, D.R., Arvesen, J., Sutton, P., Small, C., Nemani, R., Longcore, T., Rich, C., Safran, J., 2007a. The Nightsat mission concept. Int. J. Rem. Sens. 28, 2645–2670.

Elvidge, C.D., Sutton, P.C., Ghosh, T., 2009. A Global poverty map derived from satellite data. Computers and Geo-science 35, 1652–1660.

Elvidge, C.D., Tuttle, B.T., Sutton, P.C., 2007b. Global distribution and density of constructed impervious Surfaces. Sensors 7, 962–1979.

Gao, B., Huang, Q., He, C., Ma, Q., 2015. Dynamics of urbanization levels in China from 1992 to 2012: perspective from DMSP/OLS nighttime light data. Rem. Sens. 7, 1721–1735.

Ghosh, T., Anderson, S., Powell, R.L., Sutton, P.C., Elvidge, C.D., 2009. Estimation of Maxico's informal economy and remittances using night time imgery. Rem. Sens. 1 (3), 418–444 2009.

He, C.Y., Ma, Q., Li, T., Yang, Y., Liu, Z.F., 2012. Spatiotemporal dynamics of electric power consumption in Chinese mainland from 1995 to 2008 modeled using dmsp/ols stable nighttime lights data. J. Geogr. Sci. 22, 125–136.

Hijmans, R.J., van Etten, J., 2011. raster: Geographic Analysis and Modeling with Raster Data. R package version 1.8-39.

Hu, N., 2016. Exploration of the development of the urban-rural fringe in Beijing under the new situation. Real Estate Inf. China 4, 51.

Hutchinson, J., Hutchinson, J., 1969. Population and food supply. BMJ Br. Med. J. (Clin. Res. Ed.) 3893 (320), 4.

Huilei, Li, Peng, Jian, Yanxu, Liu, Yi'na, Hu, 2017. Urbanization impact on landscape patterns in Beijing City, China: a spatial heterogeneity perspective. Ecol. Indicat. 82, 50–60.

János, N., 2014. Climate change, agricultural land use and food safety. Econ. Aic 7, 149–157 9.

Jenerette, G.D., Harlan, S.L., Brazel, A., Jones, N., Larsen, L., Stefanov, W.L., 2007. Regional relationships between surface temperature, vegetation, and human settlement in a rapidly urbanizing ecosystem. Landsc. Ecol. 22, 353–365.

Jing, X., Shao, X., Cao, C., Fu, X., Yan, L., 2015. Comparison between the Suomi-NPP Day-Night Band and DMSP-OLS for correlating socio-economic variables at the provincial level in China. Rem. Sens. 8, 17.

Kumar, P., Haroon, S., Alare, R., Elvidge, C., Ahmed, R., Mandal, V., 2017. Analysis of urban population dynamics based on residential buildings volume in Pakistan using operational linescan system sensors. Sensors Journal IEEE 17 (6), 1656–1662.

Levin, N., Duke, Y., 2012. High spatial resolution night-time light images for demographic and socio-economic studies. Remote Sens. Environ. 119, 1–10.

Li, L., Lei, Y., Pan, D., Si, C., 2016. Research on sustainable development of resource-based cities based on the DEA approach: a case study of Jiaozuo, China. Math. Probl Eng. 3, 1–10.

Li, X., Chen, X., Zhao, Y., Xu, J., Chen, F., Li, H., 2013a. Automatic intercalibration of night-time light imagery using robust regression. Remote Sens. Lett. 4, 45–54.

Li, X., Xu, H., Chen, X., Li, C., 2013b. Potential of NPP-VIIRS nighttime light imagery for modeling the regional economy of China. Rem. Sens. 5, 3057–3081.

Liu, Z., He, C., Zhang, Q., Huang, Q., Yang, Y., 2012. Extracting the dynamics of urban expansion in China using DMSP-OLS nighttime light data from 1992 to 2008. Landsc. Urban Plann. 106, 62.

Lo, C.P., 2001. Modeling the population of China using DMSP operational linescan system nighttime data. Photogramm. Eng. Rem. Sens. 67, 1037–1047.

Lu, D., Tian, H., Zhou, G., Ge, H., 2008. Regional mapping of human settlements in southeastern China with multisensor remotely sensed data. Remote Sens. Environ. 112, 3668–3679.

Ma, T., Zhou, C., Tao, P., Haynie, S., Fan, J., 2014. Responses of Suomi-NPP VIIRS-derived nighttime lights to socioeconomic activity in China's cities. Remote Sens. Lett. 5, 165–174.

Ma, T., Zhou, C.H., Pei, T., Haynie, S., Fan, J.F., 2012. Quantitative estimation of urbanization dynamics using time series of DMSP/OLS nighttime light data: a comparative case study from China's cities. Remote Sens. Environ. 124, 99–107.

Ma, T., Zhou, Y., Zhou, C., Haynie, S., Pei, T., Xu, T., 2015. Night-time light derived estimation of spatio-temporal characteristics of urbanization dynamics using DMSP/OLS satellite data. Remote Sens. Environ. 158, 453–464.

Miao, C.L., Sun, L.Y., Yang, L., 2016. The studies of ecological environmental quality assessment in Anhui Province based on ecological footprint. Ecol. Indicat. 60, 879–883.

Milesi, C., Elvidge, C.D., Nemani, R.R., Running, S.W., 2003. Assessing the impact of urban land development on net primary productivity in the southeastern United States. Remote Sens. Environ. 86, 401–410.

National Bureau of Statistics of China, 2017. China Statistical Yearbook. Available online: http://www.stats.gov.cn/english/statisticaldata/AnnualData/, Accessed date: 12 March 2017.

Obienusi, E.A., Ekezie, M., Onwuka, S.U., 2014. Investigating the place of population increase and level of income earning in food security a study of yam supply in Awka urban, Anambra state of Nigeria. J. Nat. Sci. Res. 11, 11–21.

Pan, R., Liu, Y., Sun, H., 2016. The coupling analysis of population urbanization and economic development: take the case of counties (Cities, Areas) of Henan Province. Geomat. Spat. Inf. Technol. 3, 85–89.

Pandey, B., Joshi, P.K., Seto, K.C., 2013. Monitoring urbanization dynamics in India using DMSP/OLS night time lights and SPOT-VGT data. Int. J. Appl. Earth Obs. Geoinf. 23, 49–61.

Raupach, M.R., Rayner, P.J., Paget, M., 2010. Regional variations in spatial structure of nightlights, population density and fossil-fuel CO2 emissions. Energy Pol. 38 (9), 4756–4764.

Small, C., Pozzi, F., Elvidge, C.D., 2005. Spatial analysis of global urban extent from DMSP-OLS night lights. Remote Sens. Environ. 96, 277–291.

Sullivan, W.T., 1989. A 10 km resolution image of the entire night-time earth based on cloud-free satellite photographs in the 400–1100 nm band. Int. J. Rem. Sens. 10, 1–5.

Sutton, P.C., Anderson, S.J., Elvidge, C.D., Tuttle, B.T., ghosh, T., 2009. Paving the planet: impervious surface as proxy measure of the human ecological footprint. Prog. Phys. Geogr. 33, 510–527.

Sumita, M., 2011. Communiqué of the national Bureau of statistics of People's republic of China on major figures of the 2010 population census (No. 2). China Popul. Today 6, 24–25.

Sutton, P., 1997. Modeling population density with night-time satellite imagery and GIS. Comput. Environ. Urban Syst. 21 (3/4), 227–244.

Sutton, P., Roberts, D., Elvidge, C., Melj, H., 1997. A comparison of nighttime satellite imagery and population density for the continental United States. Photogramm. Eng. Rem. Sens. 63, 1303–1313.
Tripathi, Bismay R., Tiwari, V., Pandey, V., Elvidge, C., Rawat, J.S., Sharma, M.P., Pravasi, R., Kumar, P., 2017. Estimation of urban population dynamics using dmsp-ols night-time lights time series sensors data. Sensor. J. IEEE 17 (4), 1013–1020.
Tripathy, B.R., Sajjad, H., Elvidge, C.D., Ting, Y., Pandey, P.C., Rani, M., Kumar, P., 2018. Modeling of electric demand for sustainable energy and management in India using spatio-temporal dmsp-ols night-time data environmental management. 61 (4), 615–623.
United Nations (UN), 2015. World Urbanization Prospects: The 2014 Revision. UN, New York, NY, USA.
Wang, C., Liu, Y., Kong, X., Li, J., 2017. Spatiotemporal decoupling between population and construction land in urban and rural Hubei province. Sustainability 7, 1258.
Witmer, F., O'Loughlin, J., 2011. Detecting the effects of wars in the caucasus regions of Russia and Georgia using radiometrically normalized DMSP-OLS nighttime lights imagery. GIScience Remote Sens. 48, 478–500.
Wu, J., He, S., Peng, J., Li, W., Zhong, X., 2013. Intercalibration of DMSP-OLS night-time light data by the invariant region method. Int. J. Rem. Sens. 34, 7356–7368.
Xu, T., Ma, T., Zhou, C., Zhou, Y., 2014. Characterizing spatio-temporal dynamics of urbanization in China using time series of DMSP/OLS night light data. Rem. Sens. 6, 7708–7731.
Yigzaw, W., Hossain, F., 2016. Water sustainability of large cities in the United States from the perspectives of population increase, anthropogenic activities, and climate change. Earths Future 12, 603–617.
Yu, B.L., Shu, S., Liu, H.X., Song, W., Wu, J.P., Wang, L., Chen, Z.Q., 2014. Object-based spatial cluster analysis of urban landscape pattern using nighttime light satellite images: a case study of China. Int. J. Geogr. Inf. Sci. 28, 2328–2355.
Zeng, C., Zhou, Y., Wang, S., Yan, F., Zhao, Q., 2011. Population spatialization in China based on night-time imagery and land use data. Int. J. Rem. Sens. 24, 9599–9620.
Zhang, Q., Hao, Y., 2007. Analysis of income distribution gap of the residents in urban-rural fringe. Prod. Res. 2, 88–89.
Zhang, Y., 2015. Research on the effects of changes in the age structure of China's population to energy consumption: based on the provincial dynamic panel data by GMM. China Popul. Resour. Environ. 11, 69–74.
Zhuo, L., Ichinose, T., Zheng, J., Chen, J., Shi, P.J., Li, X., 2009. Modelling the population density of China at the pixel level based on dmsp/ols non-radiance calibrated night time light images. Int. J. Rem. Sens. 30, 1001–1018.